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Measuring and Monitoring of Education Infrastructure of Southern Federal District of the Russian Federation

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Abstract

The purpose of this research is to measure and track trends in education infrastructure of federal subjects of southern federal district by presenting a latent trait approach to data collected by Federal State Statistics Service of the Russian Federation. In this paper, education infrastructure indicators are modeled as questionnaire items, and frequency and continuous integer values are recoded categorically for analysis with a Rasch model for rating scales. This research demonstrates applicability of Rasch models to frequency and continuous integer values by constructing a common dimension for both regions and infrastructure indicators. These results suggest the traditional method of comparing federal subjects with separate indicators may not be taking full advantage of information reported by Federal State Statistics Service. When infrastructure indicators were consolidated into a coherent latent trait, it is available to compare and monitor educational infrastructure at federal subjects level.

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Keywords: education infrastructure; latent variable; Rasch measurement; interval scale; monitoring

1. Introduction

The Federal State Statistics Service of the Russian Federation annually collects data from federal subjects about education infrastructure across a broad range of indicators about preschool, general, and high educational organizations, student and graduate enrollment, as well as teachers (Regioni Rossii. Socialno-economicheskie pokazateli, 2014). Because these indicators are collected as frequencies and continuous integers (number of

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organizations, students, graduates, teachers, and so on), amount of collected data is typically enormous. Currently, The Federal State Statistics Service summarizes the education infrastructure of a subject by separate descriptive statistics for each indicator. Unfortunately, with this approach, it is difficult to summarize a subject's education infrastructure over all the indicators, and to directly compare a subject's education infrastructure between different years, and to compare education infrastructure between different subjects (Maslak & Anisimova, 2001). If a measurement scale can be established with the Rasch model, then it is possible to represent each subject's education infrastructure by a single measure. Such a single measure would, among other things, facilitate a subject's education infrastructure to be monitored, enable a comparison of education infrastructure between different subjects, information that would help improve a subject's education infrastructure (Rasch, 1960).

The aggregation methods to summarize indicators with statistics and indices are very complicated and meaningfulness of ratios and weighted averages based on them is not always apparent. Besides it aggregated data are not linearized hence measurement properties of compiled statistics and indices are unknown.

2. Objectives

The purpose of this research is to measure and monitor education infrastructure in federal subjects based on frequency summaries by presenting a latent trait approach to data collected by the Federal State Statistics Service. Although latent trait theory has been successfully applied to frequency data, large volumes of continuous integer data, empirical examples are still rare. In this report, infrastructure indicators are modeled as questionnaire items, and frequency and continuous integer values are recoded categorically for analysis with a Rasch model for rating scales (Álvarez, 2005).

3. Research questions

This research explores the possibility that indicators of education infrastructure may coherently define a latent trait with linear measurement properties. In this context, the following questions were addressed:

1. Can statistical frequency and continuous integer data be reformulated for categorical analysis with a Rasch model for rating scales?

2. Do education infrastructure indicators after coding and transformation with a Rasch model have linear measurement properties?

3. Does formulation of education infrastructure construct offer any benefits to policy analysis?

4. Methodology and research design

Population. The entire population of federal subjects of the Southern Federal District of the Russian Federation is included in this research. The federal regions are Republic of Adygea, Astrakhan Oblast, Volgograd Oblast, Republic of Kalmykia, Krasnodar Krai, and Rostov Oblast.

Data. Data consists of frequency counts and continuous integer values for 24 indicators reported by Federal State Statistics Service for 2010 - 2013 years. These indicators of education infrastructure are presented in Table 1. For adequate comparison of federal subjects' education infrastructure estimates of all of these indicators are given per 10000 population.

For the purpose of the investigation, especially of monitoring federal subjects, as measurement objects there are considered combination of subject x year. So there are 6 x 4 measurement objects.

Table 1. Indicators of education infrastructure

No	Indicators of education infrastructure
1	Preschool educational organizations
2	General educational organizations
3	Students in state and municipal general educational organizations

4	Students graduated from the state and municipal general educational organizations
5	Students graduated from the state and municipal general educational organizations with the certificate about the average general education
6	Teachers in the state and municipal general educational organizations
7	Professional educational organizations which are carrying out preparation of qualified workers and employees
8	Students trained under programs of preparation of qualified workers and employees
9	Students taking programs of education for the qualified workers and employees
10	Graduated qualified workers and employees
11	Teachers in the professional educational organizations which are carrying out education of qualified workers and employees
12	Masters in the professional educational organizations which are carrying out education of qualified workers and employees
13	Professional educational organizations which are carrying out pre-high education
14	Students trained under programs of preparation of pre-high education
15	Students enrolled on training under pre-high education programs
16	Pre-high education graduates
17	Teachers engaged in pre-high education organizations
18	Students engaged in state and municipal pre-high educational organizations
19	Educational organizations of higher education
20	Branches of educational organizations of higher education
21	Students trained under bachelor, speciality and master degree programs
22	Students enrolled on training under bachelor, specialty and master degree programs
23	Professorial personnel in organizations of higher education
24	Personal computers used for the educational purposes, in the state and municipal general educational organizations

Coding. The Rasch model assumes item responses to be ordinal and discrete. So for each of the indicators the continuous response scale was initially discretized into a rating scale. In particular, for each of these indicators, there was constructed rating scale by taking the range of the responses observed over all objects in the data, and dividing that range into equal parts. Several initial runs of Rasch analysis were performed in the data collected by Federal State Statistics Service of the Russian Federation to determine the optimal number of categories for each of the indicators. Over all these runs, it was determined that the choice of four rating categories for all indicators maximized the region separation index to .86. So in all subsequent Rasch analyses, these categorizations for the indicators are assumed.

These data were coded for empirical analysis with the following algorithm:

Step	Raw data = categorical data
1)	0 to 25th percentile = 0
2)	26th to 50th percentile = 1
3)	51st percentile to 75th percentile = 2
4)	Greater than 75th percentile = 3

Analysis. Coded frequencies were transformed to linear measures with a Rasch model for rating scales, which computes a log-odds transformation of indicators and objects, then computes differences between indicators and objects also guided by the one-parameter logistic function to establish a common dimension (Letova, Maslak, Osipov, 2013; Maslak, Karabatsos, Anisimova, Osipov, 2005; Wright & Masters, 1982). A simple mathematical model is implemented for this transformation:

$$\Pi_{\mathrm{nix}} = \frac{exp\sum_{j=0}^{x}\left[\beta_n-\left(\delta_i+\tau_j\right)\right]}{\sum_{k=0}^{m} exp\sum_{j=0}^{k}\left[\beta_n-\left(\delta_i+\tau_j\right)\right]}$$

where β_n = region's location parameter on the education infrastructure latent trait,
δ_i = indicator location parameter on the latent trait, and
τ = rating scale thresholds.

Π_{nix} is the probability that any indicator δ_i will be coded X for any object β_n where X takes a value from a fixed range (j = 0, 1, 2, 3), m = number of steps for an indicator, and k = i_{th} step. The conformability of raw data to mathematical expectations was assessed with a Chi-square derived fit analysis of indicator and institutions residuals (Wright & Masters, 1982).

For data processing there was used RUMM2020 software (Andrich, Sheridan, Luo, 2005). An ANOVA then was conducted to investigate differences between regions and years (Markova & Maslak, 1986; Maslak, 1988).

5. Research outcomes

Fit analysis. There are presented item characteristic curves for two distinguishing items: the best and least fitting indicators to the Rasch rating scale model.

Figure 1 elaborates the results of the best fitting indicator 2, which has a chi-square fit statistic having a p-value of .907.

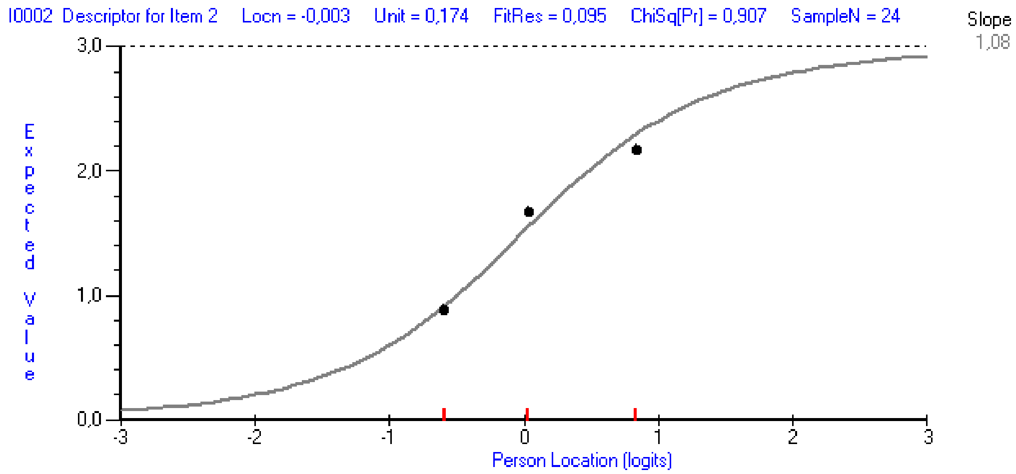

Fig. 1. Item characteristic curve for the best fitting indicator 2 “General educational organizations”

In Figure 1, each of the three points represents the mean response of objects on indicator 2 “General educational organizations”, with respect to the “low”, “medium,” and “high” category on the β scale, respectively. Recall that β represents a measure of education infrastructure. The line in the Figure 1 represents the predicted response of the Rasch model, as a function of β, in other words, the estimated item characteristic curve (ICC). It could be seen from this figure that the points lie very close to the estimated ICC for indicator 2.

Figure 2 presents the mean responses, and the estimated ICC for indicator 19 “Educational organizations of higher education”. This indicator has the worst fit to the Rasch model, with a chi-square p-value less than .001. It could be seen from the Figure 2 that the observed mean responses lie far from the estimated ICC. Not only that, the mean response appears to be a *decreasing* function of education infrastructure β. While it is widely accepted in education that a big number of universities corresponds to higher education infrastructure, we see evidence here of the opposite, that a small number of universities (that is, a lower mean response) corresponds to a higher level of education infrastructure β. This indicator is the only other item that misfit the Rasch model, with a chi-square fit statistic having a p-value less than .001. Given that the item is misfitting under the Type I error rate of .05, it was of interest to determine whether the omission of this item produces any significant changes in the country measures on the β scale. So, there were compared two sets of estimated object measures. The first set of measures excludes indicator 19, while the second set of measures includes this indicator. It was shown that the omission of indicator 19 does not produce any meaningful differences in object measures; in fact the Pearson correlation between the two sets of measures equals .996. This can be explained that important information about education infrastructure contained in other indicators.

So the final decision was to retain all indicators for the scale of education infrastructure, with exception to indicator 19.

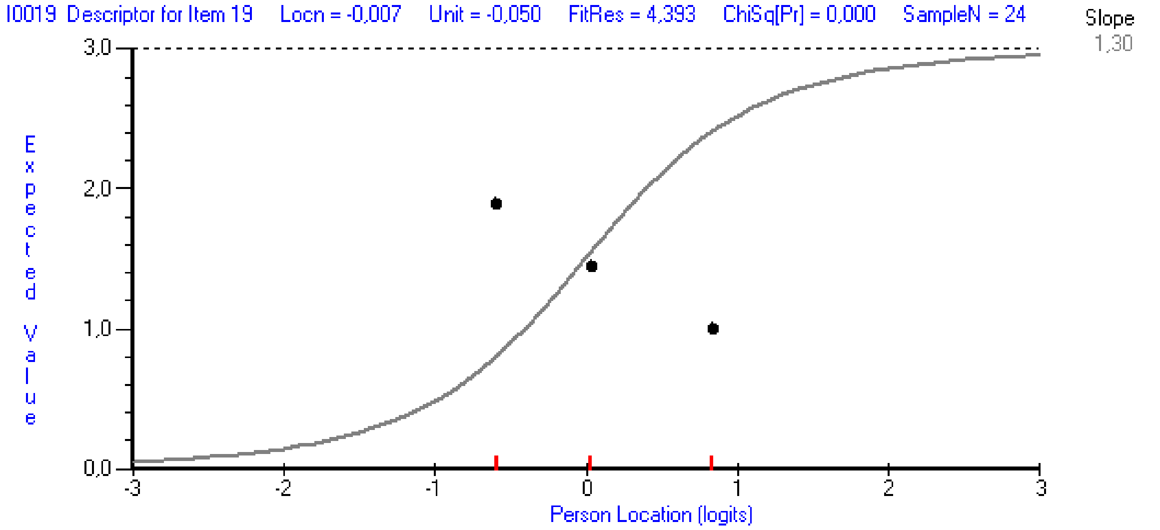

Fig. 2. Item characteristic curve for the least fitting indicator 19 "Educational organizations of higher education"

Construct interpretation. Figure 3 presents a map of indicators and objects after transformation to a common dimension.

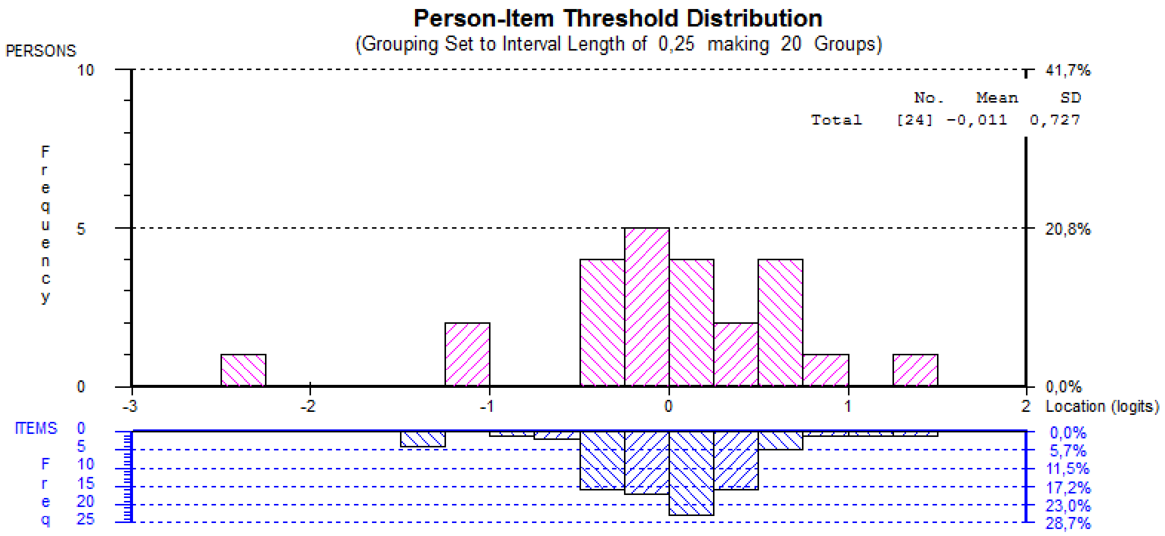

Fig. 3. Map of objects and indicators on the education infrastructure scale

In Figure 3 persons correspond to objects and items correspond to indicators. These results show education infrastructure indicators well-targeted on objects without ceiling or floor effects.

Measurement properties. Indicators, in general, appear to distribute well across the latent trait with a concentration at mid-scale. Results show indicators targeted the objects with a range between -1,50 and 1,50 logits, SD = .33. Objects' education infrastructure distribute from -2,50 to 1,50 logits. Mean of objects' education infrastructure equals -.01, SD = .73. Although data variability is modest, SD = .73, object separation index as it was noted is high and equals .86.

Education infrastructure variation by subject and year. There was conducted ANOVA of education infrastructure depending on the subject and year. In Table 2 there are presented results of two-way ANOVA of education infrastructure depending on the subject and year.

Table 2. Results of two-way ANOVA of education infrastructure depending on the region and year

Source of variation	Sum of squares	Degrees of freedom	Mean sum of squares	F	p
Subject	10.261	5	2.052	18.015	<.001
Year	4.025	3	1.342	11.777	<.001
Error	1.709	15	.114		
Total	16.006	24			

The results presented in Table 2 show that education infrastructure differed significantly by subjects and years. Table 3 presents the subjects' level of education infrastructure on the average in 2010 - 2013 years. The highest level of education infrastructure (1.178 logits) has Republic of Kalmykia, quite unexpected highly developed Krasnodar Krai shows the least level of infrastructure (-1,049 logits).

Table 3. Level of education infrastructure of subjects of the Southern Federal District

Subject	Level of education infrastructure (logits)	Standard error (logits)	95% confidence interval	
			Low boundary	Upper boundary
Republic of Adygea	.068	.169	-.292	.427
Astrakhan Oblast	.188	.169	-.172	.547
Volgograd Oblast	-.192	.169	-.552	.167
Republic of Kalmykia	1.178	.169	.818	1.537
Krasnodar Krai	-1.049	.169	-1.409	-.689
Rostov Oblast	-.062	.169	-.422	.297

Estimates of level of education infrastructure depending on year on the average of all regions of the Southern Federal District are presented in Table 4.

Table 4. Estimates of education infrastructure of the Southern Federal District in 2010 - 2013

Year	Level of education infrastructure (logits)	Standard error (logits)	95% confidence interval	
			Low boundary	Upper boundary

2010	.602	.138	.309	.896
2011	.091	.138	-.203	.384
2012	-.061	.138	-.355	.233
2013	-.546	.138	-.840	-.252

Table 4 shows the level of education infrastructure decreased significantly from .602 logits in 2010 to -.546 logits in 2013. The Jonckheere test demonstrates that this decrease is statistically significant at the Type I error rate of $\alpha = .001$ (Jonckheere, 1954).

6. Discussion

This research appears to be the first attempt to construct a unidimensional scale for measuring the education infrastructure of the regions. Practice has shown that there is a danger in drawing too many conclusions from changes in a single indicator, or from its relationship to other variables. This fact is illustrated by the well-known indicator as number of universities in the region (per population). It appears that the importance of the number of universities in the region for measuring of education infrastructure is somewhat exaggerated. Perhaps this means that, in practice, smaller number may need to be weighed against higher number of students and teachers in the region.

Compared with the approach to evaluating education infrastructure by interpreting the raw observations on a single indicator, or the raw responses of each of the multiple indicators separately, the Rasch model approach to measuring education infrastructure has several important advantages. First, a single measure of education infrastructure can be constructed from a large number of different indicators. Second, the estimated Rasch measures are on a linear scale, so it is possible to quantitatively compare and monitor the different regions in terms of education infrastructure. Third, more indicators lead to greater precision of measurement of the regions. The analysis of estimates of education infrastructure has depicted that estimates are stable enough and are not much influenced by excluding any of indicators. It is shown that official statistics of the Federal State Statistics Service of the Russian Federation are compatible in a high degree, and therefore together can be used for measuring a region's education infrastructure. Fourth, the estimated measures are successfully used for monitoring education infrastructure in the subjects, and for providing information useful for making decisions in educational policy.

This research demonstrates applicability of Rasch models to frequency and continuous integer values by constructing a common dimension for both subjects and infrastructure indicators. These results suggest the traditional method of comparing regions with separate indicators may not be taking full advantage of information reported from education infrastructure in Russia. When infrastructure indicators are consolidated into a coherent latent trait, the analysis of education infrastructure is more powerful. In this research, there are explored the axiomatic properties of this latent trait structure and found good conformity to measurement model expectations. The measurement properties of indicators after consolidation appear adequate for practical applications with policy and implications.

A property of this framework not yet discussed is the foundation for objective annual comparisons of subjects, because parameters are not dependent on specific sample distributions. In other words, once the framework is defined by indicators, it transcends specific samples offering the possibility of absolute measurements. A mathematical assertion is the relations between indicators and subjects represent abstract relations, which have axiomatic properties when data fit the Rasch model. Consequently, the framework offers an explicit standard or benchmark for evaluation and standards.

7. Conclusion

An important limitation of this approach is the arbitrary selection of indicators. While content categories clearly show face validity, substitution or addition of other indicators may alter the obtained hierarchy. Likewise, the generalizability of the obtained indicator hierarchy is currently limited to education infrastructure in Russia. The generality of this hierarchy, however, will become more apparent as international comparison studies are conducted. Another limitation is that the research suffers from lack of access to external validity criteria.

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